Ecosystem Monitoring and Port Surveillance Systems

Using Passive & Active Acoustics and Data Fusion

A. Mansour[*1], I. Leblond[2]

Lab-STICC, ENSTA Bretagne, 2 Rue François Verny, 29200 Brest, France

[*1]mansour@ieee.org; [2]isabelle.leblond@ensta-bretagne.fr

Abstract

In this project, we should build up a novel system able to perform a sustainable and long term monitoring coastal marine ecosystems and enhance port surveillance capability. The outcomes will be based on the analysis, classification and the fusion of a variety of heterogeneous data collected using different sensors (hydrophones, sonars, various camera types, etc). This manuscript introduces the identified approaches and the system structure. In addition, it focuses on developed techniques and concepts to deal with several problems related to our project. The new system will address the shortcomings of traditional approaches based on measuring environmental parameters which are expensive and fail to provide adequate large-scale monitoring. More efficient monitoring will also enable improved analysis of climate change, and provide knowledge informing the civil authority's economic relationship with its coastal marine ecosystems.

Keywords

Underwater Ecosystem; Passive and Active Acoustics; Signal Processing; Blind Source Separation; Blind Identification and Localisation Problems; Data Fusion

Project Description

Oceans play an enormous part in the climate, in the global as well as the local economical system (transportation, food reserve, *etc*). Recently, oceanography, marine bio-systems and ecosystems have been the priority for many researchers all around the world. In addition, oceans' ecosystem has a major impact on the earth ecosystem. Metropolitan France borders the Bay of Biscay, the Celtic Sea and English Channel, between Belgium and Spain, southeast of the UK; and the Mediterranean Sea, between Italy and Spain. With 3,427 km of coastlines in metropolitan France, our study can obviously be of great national interest. In fact, the coastal marine ecosystem could play an important role in future France and worldwide economy and sociology. Monitoring coastal marine ecosystem leads us to analyse climate changes, to study ecological parameters, and to estimate economical factors. To study coastal marine ecosystem various environmental parameters should actually be measured. This approach suffers from high cost and fails to provide adequate large scale monitoring. Therefore, it is necessary to undertake thorough monitoring of France's coastal marine ecosystems to ensure that they are healthy and their economic use is sustainable.

In this project, we are proposing an original approach based on the analysis and classification of variety of heterogeneous data collected using different sensors (such as hydrophones, fisheries echosounder, ADCP, sidescan sonar, cameras, etc.). The success of our project requires an automatically process of the huge database, to develop and apply new classification algorithms along with image processing, blind signal processing and automatic feature extraction tools.

Data should be recorded with the help of an underwater cabled observatory containing all the sensors used in the study. Fig 1 shows a schematic view of the surveillance system.

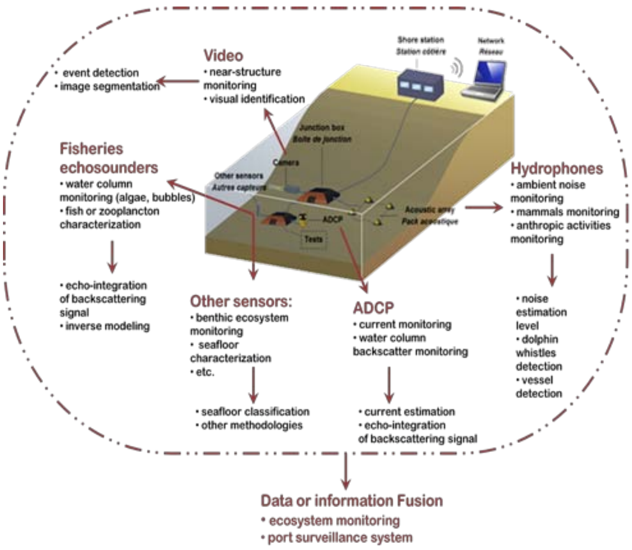


FIG. 1 SCHEMATIC OF OUR SURVEILLANCE SYSTEM

To achieve our goals, we are planning to use advanced

signal processing algorithms (including but not limited to, adaptive filters, blind recognition, identification, and source separation), High Order Statistics (HOS), multi-scale representations, and unsupervised classification along with neural networks. These algorithms should be adapted in order to include new applications and deal with hostile environments. It is worth mentioning that in the last two decades and through several previous projects, we have been involved in many real life applications and published a large amount of different studies which showed the capacities of our algorithms to deal with various non-stationary signals and a large set of complex images obtained in different scenarios, such as:

- Biomedical Engineering: magnetic resonance imaging, electroencephalogram, electrocardiogram, electromyography are very noisy non-stationary weak signals that suffer from artefact and non-linear filtering problems. In previous projects, a couple of algorithms was proposed to filter these signals and extract patterns and useful features.
- Auditory Scene Analysis (ASA): In this scenario, the treated signals (such as speech, music, noise, etc.) are highly non-stationary signals.
- Electronic Warfare: several contributions were proposed to deal with these up-to-date and challenging problems. In COMmunication INTelligence (COMINT) applications, few assumptions about the intercepted signals can be satisfied. Prior information is not always available. However, if it is possible to get prior information that has been used to improve the performance of our algorithms.
- Passive Oceanic Tomography (PAT): we have applied recent signal processing methods to develop PAT methods mainly for economical and ecological purposes.
- Seafloor characterization: we developed a multiscale approach with wavelet tools to obtain an accurate segmentation and classification of the seafloor sidescan images.
- Mine hunting: we improved a multiview classification system of sidescan images.
- Fisheries acoustics: we adapted approaches used in fisheries acoustics (use of split-beam echosounders, use of data such volume backscattering strength or echo-integration results, adaptation of inverse modelling methodologies, etc.) to varied situation such algae monitoring in water column or bubbles seeps flows estimation in water column.

It should be mentioned here that underwater acoustic signals are highly non-stationary and sparseness signals. The latest properties are a common factor among our previously treated signals (i.e. speech signals, bio-medical signals, underwater acoustic signals used in PAT or sonar images). A main goal of our project consists on developing unsupervised classification algorithms along with unsupervised signal processing tools. Simulations and experimental studies will be conducted to corroborate our developed algorithms.

This project is a pioneer multi-disciplinary project. In fact, the success of our project requires a deep knowledge of various research axes such as: information theory, advanced signal processing and image processing algorithms (blind identification and separation methods, wavelets, time-frequency-phase representations, shape extraction algorithms, adaptive filters, etc.), unsupervised classification and pattern recognition approaches, without neglecting the essential part of data fusion. In addition, this project requires the collection and the process of huge amount of data. Data fusion approaches should be developed to achieve the final stage of our project which is the prediction and the decision making.

Our research project will operate and process information from several different sensors, passive and active acoustics, or video. The primary aims are to achieve a better understanding of the information obtained from each sensor, including hydrophones, and to offer the ability of complete systems such as monitoring applications ecosystems or human type monitoring port. The project thus defined is both a great academic challenge (development of new algorithms) that requires the use of large technical means based on new technology (the use, design or proposed platforms). From an academic perspective, several challenging problems should be addressed. Major problems have been discussed in this manuscript.

Approaches and Methodology

The analysis of various images and signals obtained from any ecosystem or bio-system is very challenging due to the complexity of the images, and the non-stationarity and sparness of the signals. Our main task will be the development of appropriate pre-processing signal and image algorithms as well as the elaboration of unsupervised classification methods.

Recently, two research axes have been raised in the field of signal processing: Blind identification and separation approaches, and multi-scale representations (time-frequency representations or wavelet analysis). The blind separation of sources (BSS) problem consists in retrieving unknown sources from only observing a mixture of them. BSS was initially proposed to study biological phenomena (i.e. the central nervous system processes typically multidimensional signals). Recently, BSS can be found in various situations: radio-communication, speech enhancement, separation of seismic signals, noise removal from biomedical signals, etc. In previous work [Barros et al. NeuroComputing 1998] related to bio-medical signals, we proposed an approach based on BSS. In fact, the Independent Component Analysis (ICA) which is the basic of BSS can be considered as a powerful projection of our observed signals into a new space more appropriate to extract information, see Fig 2.

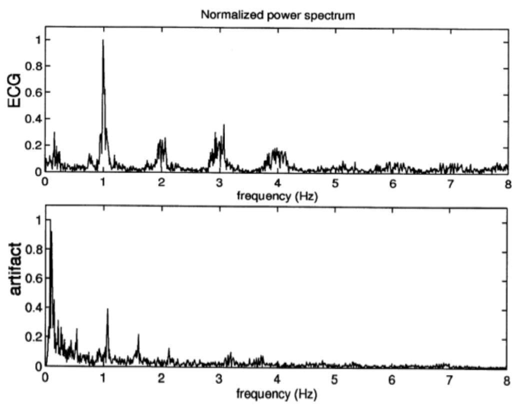


FIG. 2 POWER SPECTRUM OF THE TWO SOURCE SIGNALS: ECG AND ELECTRODE MOTION ARTEFACT. NOTICE THAT THE FIRST HARMONIC OF THE ECG SIGNAL (AROUND 1HZ) IS OVERLAPPED IN FREQUENCY BY THE RESPIRATORY ONE. (THIS FIGURE EXTRACTED FROM OUR PREVIOUS STUDY PUBLISHED AT NEURCOMPUTING 1998)

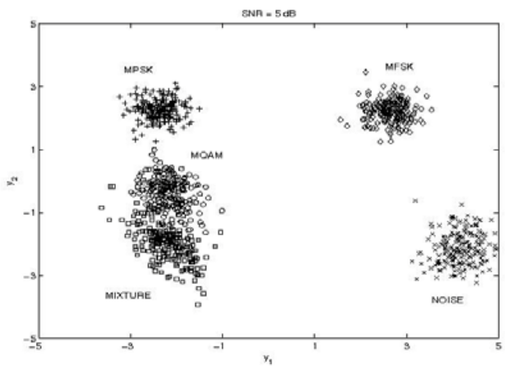


FIG. 3 CLASSIFICATION OF INTERCEPTED DIGITAL SIGNALS. (THIS FIGURE EXTRACTED FROM OUR WORKS PUBLISHED AT ICA 2004)

Using High Order Statistics (HOS), information theory along with multi-scale analysis, we proposed various algorithms to classifying and recognizing noisy digital communication signals; see Fig 3. In the actual project, it is aimed to apply BSS and HOS to pre-process a variety of underwater acoustic signals.

In order to obtain a better knowledge of the nature of the seafloor, a multiscale segmentation and classification algorithm on textured sidescan sonar image were put forward, using parameters coming from a wavelet analysis. Fig. 4 shows an example of the result of the sonar classification.

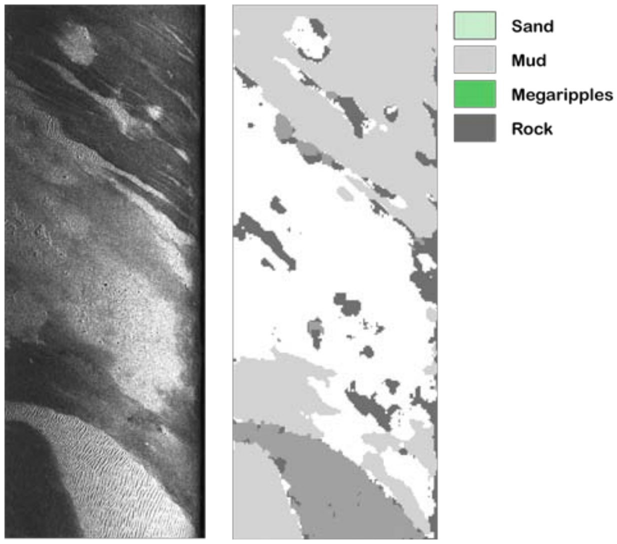


FIG. 4 EXAMPLE OF SIDESCAN SONAR IMAGE (KLEIN 5000, DATA FROM GESMA) AND RESULTS OF THE SEGMENTATION AND CLASSIFICATION [LEBLOND ET AL. 2005] [LEBLOND ET AL. 2008]

Another project, using multiview classification and fusion was used to improve the classification of sonar images of mines. The originality of this study consisted in the automatic choice of the additional views using a predictive tool based on the estimation of the angle of view. Fig. 5 gives a schematic view of the approach [Leblond et al. 2010].

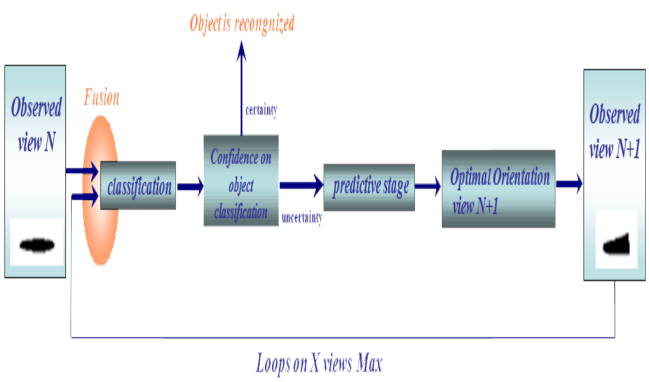


FIG. 5 SCHEMATIC OF THE MULTIVIEW CLASSIFICATION METHODOLOGY [LEBLOND ET AL. 2010]

In another study, we used data recorded in the water column by a split-beam echosounder. Parameters computed on features automatically extracted from nautical area scattering coefficient were used to provide a segmentation and classification in order to obtain a prediction of algae abundance in a channel. Fig. 6 shows an example of result of the prediction algorithm.

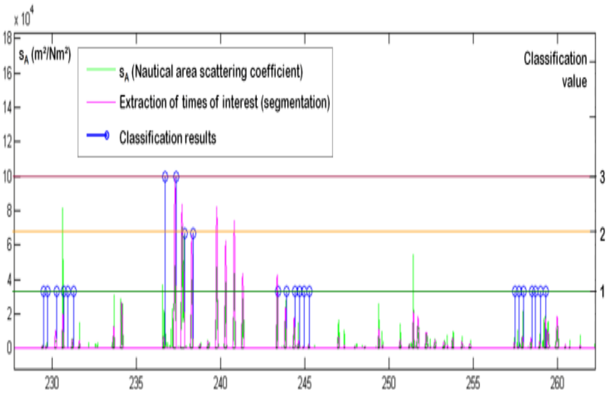


FIG. 6 NAUTICAL AREA SCATTERING COEFFICIENT COMPUTED ON ACOUSTIC DATA OF ALGAE IN THE WATER COLUMN, SEGMENTATION OF INTEREST PERIODS AND CLASSIFICATION RESULTS OF ALGAE ABUNDANCE IN A CHANNEL (CLASSIFICATION VALUE = 1 ⇒ NO MUCH ALGAE, VALUE = 2 ⇒ MORE ALGAE, VALUE = 3 ⇒ CRITICAL PRESENCE OF ALGAE) [LEBLOND ET AL. 2010B]

Data visualization methods have received more attention from electrical and computer engineering community: Image indexation and retrieval, data mining, surveillance, diagnosis, etc. To solve the latest problems, new projection methods in statistics and machine learning have been introduced. Most of these methods use assumptions based on geometrical or probabilistic characteristics of the data. On the other hand, pattern classification consists on representing data on computer screen. Expert feedbacks in the classification process have many advantages: Visual representations could help making more confident decisions and feedbacks may improve the whole classification process. In our project, a blind classification of collected images and signals will be a main step to help making decision. Each signal or image could be represented by a set of points in a multi-dimensional space. In this case, pertinent features of these images and signals should be firstly extracted. Later on, they should be projected in lower dimension space to reduce the computing time and efforts. To reduce the feature dimension, we will use non-linear approaches such as (Kernel PCA, ISOMAP, Locally Linear Embedding, Independent Component Analysis, etc.) and we will propose similarity criteria.

This part of our project will be mainly approached along five research axes:

- The extraction of relevant information often requires a deep knowledge of the measurement methods and the biological as well as the bio-optical characteristics of the local environment. This step could be very useful to optimally extract and represent significant features.
- Once the signals and the images have been collected and relevant information has been well defined. The main part becomes the development of projection methods along with blind classification approaches.
- To reach our final goal, new extraction and recognition and classification algorithms will be proposed using adaptive filtering theory, high order statistics, independent component analysis, wavelet, and time-frequency representations.
- In order to better detect and treat the microscopic or macroscopic images, new image processing approaches will be developed to analyse the outcomes of a sensitive high speed micro or macro cameras which will be installed.
- Sensitive satellite images of invisible lights could be also considered at a later stage in the project, to enhance the outcomes of our approaches and helping us monitoring a wide area. Specific focuses will be done in:
  - Development of algorithms for improving the estimation of sediments and resuspended sediments in the water column. This effort will require sample collection, filtering and measurement of optical scattering properties.
  - Development of algorithms that will enable the use of remotely sensed data.

Topics and research studies related to image processing part of our project are outside the scope of this journal. Even though, this part of our studies will be mentioned in the following. However, algorithm details and experimental results will be omitted. More attention will be paid to the active or passive acoustic sensors, as well as signal processing and classification. First of all, a model for an underwater acoustic transmission channel is discussed; problems related to active and passive acoustics are also considered. Classification and features extraction techniques are introduced. Topics related to data fusion are also proposed. Finally, conclusions and future works are

given at the end of the manuscript.

Inverse Modelling Methodologies in Echosounder Data

In acoustic fisheries, estimation of fish species, size and abundance is currently realized by inverse modeling on acoustic data. These data are recorded from a calibrated single or multibeam echosounder which are giving echograms of volume backscattering strength (Sv in the formalism current used [MacLennan et al. 2002]) in the water column and, if they are split-beam, target strengths (TS) of isolated targets.

If concentration of targets (fishes) is considered not to be too important (= we are in the linear domain, condition generally satisfied), a general equation relies on the volume backscattering strength to the contribution of one target:

$$s_v = \int \sigma_{bs} n(a) da \tag{1}$$

Where s_v (in m^{-1}) is the volume backscattering strength, σ_{bs}(in m^2) is the acoustic backscattering cross-section of one target of size *a* and n(a) is the concentration of targets of size *a*.

s_v is often given in dB: S_v=10 log10(s_v) (dB re 1m^{-1}), as well as σ_{bs}: TS = 10 log10(σ_{bs}) (dB re 1m^2).

A general framework is currently applied in acoustic fisheries in order to obtain an evaluation of fish stocks: estimation of volume backscattering strength on large distance, or by shoal using echo-integration methodologies, tracking isolated fishes using TS, modelling, etc.

This framework, traditionally used on vessels for studies on fishes can be applied in new different studies, such other targets monitoring or other configurations like observatories. Several examples can be given: the first one is the estimation of zooplankton abundance in the water column [Stanton et al. 1994, Korneliussen et al. 2009]. This requires generally the use of sounders at several high frequencies (typically 100kHz and higher), and other acoustic formulae of backscattering cross-section. Another example is the use of underwater fixed observatories, in order to have an estimation of fishes, a monitoring of algae [Leblond et al. 2010b] or a quantification of bubbles seeps flows in the water column [Leblond et al. 2013]. Fig. 7 shows an example of echogram data of bubbles seeps.

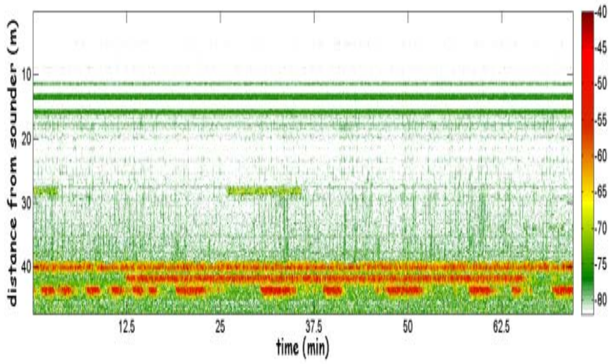


FIG. 7 ECHOGRAM OBTAINED ON NATURAL BUBBLES SEEPS IN MARMARA SEA WITH AN EK60 ECHOSOUNDER AT 120 KHZ. FOR THIS EXPERIMENT, THE EK60 INSONIFIES HORIZONTALLY [LEBLOND ET AL. 2013].

Underwater Acoustic Transmission Channel

Underwater acoustic signals could be generated by mainly three types of sources: Natural sources (waves, wind, rain, earth quack, etc.), Animal sources (such as fish, shells, dolphins, etc.), Human activities (such as, sonars, the noise generated by moving boats, underwater activities, fishing, etc.). These signals can't be easily classified or identified due to the wide diversity of their characteristics, some of which are Gaussian signals (wave noises), other are cyclo-stationary (boats' noises), low band spares signals (fish noise), high band signals (whales sounds for example), impulse signals (dolphins clicks, rain sounds, etc.), complex modulated chirp signals (dolphins whisles or, to a certain extent, sonars or echo sounders, etc.) and so on. Besides the complexity of signals of interest, one should take into consideration the supplementary difficulties related to the underwater acoustic transmission channels.

It is worth mentioning here that the conduction of underwater experiments is mostly expensive and involves complex logistics and very large heavy items. In order to validate our approaches, techniques and algorithms, real underwater experiments should be carried out. However, these experiments should be planned at an advanced stage of our project in order to save time and money. For these reasons, we developed a simulation model of an underwater acoustic transmission channels. In this section, this model is briefly discussed.

Underwater sounds propagate through water as a continuous change in the pressure. The propagation of the acoustic wave in a stationary medium is obtained by the wave equation:

$$\nabla^2 p + \frac{1}{c_0^2}\frac{\partial^2 p}{\partial t^2} \quad (2)$$

The last equation gives us an underwater sound propagation model. A general solution of the wave equation is very difficult to obtain. Therefore, simplified propagation models have been widely used [Etter 2001] (such as the ray theory, the mode theory, the parabolic model, the hybrid model, etc.). For coastal ecosystem monitoring or port surveillance applications, the height of the water column may change from a couple of meters up to a few hundred meters, i.e. the case of shallow water. In such scenario, the ray theory is the more appropriate propagation model. In the ray theory, the propagation channel is represented by FIR filters where the coefficients and the delays depend on the depth of the water column, the number of reflection spots, the sound speed, the topology and the nature of the seabed, the surface of the water, the salinity, underwater current, among other less important parameters. The sound speed C, (m/s), in oceans is an increasing function of temperature T, (°C), salinity S, (parts per thousand, ppt), and pressure which is a function of depth D, (in meters), [Etter 1991]:

$$C = 1449 + 4.6T - 0.05T^2 + 23*10^{-5}T^3 + 16*10^{-8}D^2 + 0.02D + (1.34 - 0.01T)(S - 35) - 7*10^{-13}TD^3 \quad (3)$$

The above equation is an empirical relationship satisfied when 0 ≤ T ≤ 30, 30 ≤ S ≤ 40, and D ≤8000. The reflected acoustic waves on the seabed or on the water surface depend on many parameters (such as the composition and the topology of the bottom, the wind, the wave frequency as well as the swell properties) [Lurton 2001, Brekhovskikh 2003]. As water surface isn't a flat surface, the reflected acoustic waves are dispersed in the space. However, in average term, reflected acoustic waves can be considered as obtained by a flat surface with absorption coefficients [Lurton 2001].

Finally to consider acoustic propagation effects, Schulkin and Marsh [Shulkin 1962] suggested that a received signal should be multiplied by a corrective coefficient p:

$$p = \frac{1}{r\sqrt[20]{e^{\alpha r}}} \quad (4)$$

Here r is a propagation distance and α stands for Rayleigh's absorption coefficient:

$$\alpha = \left(1 - 654*10^{-6} * P_w\right)\left(\frac{SAf_T f^2}{f^2 + f_T^2} + \frac{Bf^2}{f_T}\right) \quad (5)$$

where $f_T = 21.9*10^{\left(\frac{6T+118}{T+273}\right)}$ (in kHz), T is the water temperature, (°C), S = 3.5% is the water salinity, (in the ocean S≈ 35g/l), P_w is the water pressure, (in kg/m2), $A = 2.34*10^{-6}$ and $B = 3.38*10^{-6}$. Ray trajectories and sound speed profile allow us to compute propagation times. In addition, ray trajectories, water attenuation, boundaries roughness and sub-bottom properties allow us to compute the signal magnitude. From a computational view point, ray trajectory is computed by solving the 'Eikonal equation' but signal magnitude is obtained as a result of 'Transport equation' [Jensen 2000].

Active Acoustics

By their ease of propagation in the marine environment, the acoustic signals are often used as essential means of investigation in the underwater environment, whether for civil or military: hydrography, cartography, meteorology, useful information to browsers, development concepts sonar, etc. The majority of the systems are active systems: sonars, single and multi-beam echosounders, etc.

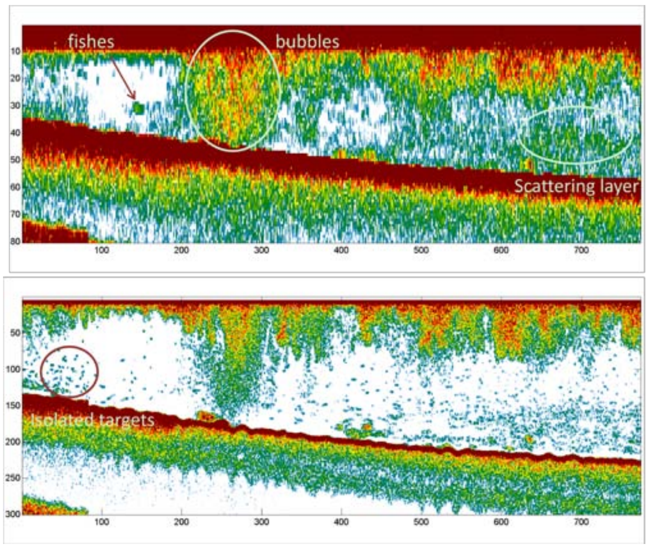


FIG.8 COMPARISON BETWEEN TWO ECHOGRAMS OF THE SAME AREA INSONIFIED BY TWO ECHOSOUNDERS AT DIFFERENT FREQUENCIES (SIMRAD EA400 AT 38 AND 200 KHZ): FISHES, BUBBLES IN SURFACE AND SCATTERING LAYERS ARE MORE VISIBLE ON THE 38 KHZ SOUNDER (TOP) BUT ISOLATED TARGETS ARE MORE DETECTABLE ON THE 200 KHZ SOUNDER (DOWN).

Active mono or multi-sounder beam, sidescan sonars or ADCP mainly suffer from the following problems:

a) Problems related to underwater acoustic propagation (acoustic refraction, attenuation of acoustic signals, the reflections on the surface of the

water or the seabed, fluctuating signals, Doppler effects, etc.).

b) Problems related to the distribution of acoustic signals by the reflectors present in the water column or on the seabed (dependence on the physical properties of signals, transmission medium, transmission frequency, multiple diffusion, interferences, speckle, etc.).

c) The formation of echoes or the backscattering signal which depends on the frequency, target shapes and materials, incidence angles, etc.

d) Interpretation of recorded signals depends on each sensor: for example, a sidescan sonar use grazing angles to insonify the seafloor when single beam sounder uses normal incidence and multibeam sounder several incidence. Many parameters could affect the interpretation, such as the frequency, the resolution, presence or not of secondary lobes, etc. Fig. 8 shows an example of two images of the same seafloor, insonified with two different sensors.

Passive Acoustics

Passive acoustic sensors can play an important role in our system. In fact, to reduce the waste of energy, to expand the life of our batteries and increase the autonomy of our system, different parts of our system will be switched on if it is needed except passive acoustic sensors which will be permanently switched on. This concept is widely used in nature; while sleeping, we close our eyes but our brain still processes the sound detected by our ears. Passive acoustic sensors are silent (don't generate any signal), no light is needed and it may detect sound arriving from all directions (cameras can only be operational in one direction at any one time). The observation ocean acoustic signals using passive, where we use the acoustic sources of opportunity exist in the environment, is relatively rare. However, this type of technology becomes more and more the center of attention of the scientific community for three main following reasons:

- A passive system is a discrete system; the importance of such quality is obvious to any military application in the context of electronic warfare.
- A transmission system, which is not part of a passive system, is often a sophisticated, bulky and expensive. Marginalization or elimination, of such a system, are economical and logistical reasons. This last reason is a big advantage for choosing a passive system for any military or civilian purposes.
- Passive systems are of interest vis-à-vis the ecology; they produce no disturbance of the ecosystem of the seabed by an emission signal.

Passive systems enjoy several advantages; however they suffer from a couple of drawbacks. An obvious disadvantage is the dependence of the system with respect to existing transmitters naturally in the environment and especially the lack of information on them. About the lack of a priori information about issuers includes mainly the number, positions and types of issuers. In addition, most of the algorithms used in passive acoustic assume the existence of a single issuer with a good signal to noise ratio. These assumptions are verified in a liability. In this case, several scenarios are possible:

- Single-Source Single-Sensor: consider the simplest case where the existence of a single source is admitted in the channel. The traditional methods of identification are the most suitable, with respect to performance and in relation to their calculation time, to deal with this case.
- Multi-Source Single-Sensor: assume that for some reason (simplicity, strategy or economics); the observation is made using only one sensor. For such a configuration, two cases are possible depending on the properties of the waveform of the signal:
  - Signals with different signatures of one dimension (i.e. straight or curved lines) in the plane of time-frequency or time-scale. In this case, algorithms based on various representations time-scale and time-frequency methods can be considered such as: the Fourier transform short-term (STFT), the spectrogram, the scalogram, the Wigner-Ville distribution pseudo Wigner-Ville distribution page, the spectrogram with signal reallocation among others.
  - Signals with the same signature or no exploitable geometrical signature (areas, volumes, dimensions higher than 1, irregular shapes, etc.) in the time-frequency or time-scale plane or space: in this case, there were no general or conventional solutions.
- Multi-Source Multi-Sensors: Here we consider the general case, i.e. a channel with multiple sources

and multiple sensors; this channel is also called Multiple Inputs Multiple Outputs or MIMO channel. Being dependent on the nature of sources considered (Gaussian or not), ICA algorithms can be used to separate different sources.

We can see the importance of treatment methods especially blind source separation algorithms to enhance existing passive acoustic. On the one hand, it should be noted here that in underwater acoustics applications, the transmission channel can be modeled as a convolutive mixture (i.e. the transmission channel between the *i*th source and the *j*th sensor can be modeled using a FIR filter). On the other hand, among the algorithms separation of convolutive mixtures, few algorithms are devoted to the treatment of non-stationary signals (a very important feature of underwater acoustic signals as natural vocalizations of whales and other marine animals, or artificial sounds as boats, submarines etc.). None of these algorithms is dedicated to the processing of real acoustic underwater signals. In the following sub-sections, the main inherited problems of passive systems are considered.

Estimation of the Number of Active Sources

In the context of underwater surveillance system, acoustic signals can be generated from various sources (natural, animal or artificial). In most cases, the number of active sources cannot be exactly evaluated[1]. However, recorded acoustic signals can be practically clustered and attributed to few generic sources (a school of fish, a commercial or military boat, waves, dolphins, so on). In any surveillance system, a rough estimation of sources is crucial. In a previous work [mansour EUROSIP2013], the estimation of source number is done by implemented existing algorithms as well as by developing new methods. Hereinafter, the previous estimation algorithms are considered and briefly discussed. It is worth mentioning that all of previous algorithms assume over-determined transmission channel, (i.e. the number of sensors, q, is strictly higher than the number of sources, p). The last assumption means that the actual algorithms can identify up to (q-1) sources. To simplify our discussion, let us consider the memoryless transmission channel case[2]. It has been shown [kailath 1980] that the number of sources can be estimated as the rank of the observation covariance matrix$\sum_X$. In fact, the first p singular values are linked to signal space and the last (q-p) ones are related to the noise space. To estimate the dimension of the noise-space, one should fix a prior threshold which depends on the Signal to Noise Ratio (SNR). As the SNR in our case is not high enough (< 5 dB), different thresholds have been proposed in [mansour EUROSIP2013]. In the same work, it was shown that proposed methods can be extended using Sylvester's matrix [mansour 2001] to deal with the case of convolutive mixtures, (i.e. memory channel which can better represent an underwater acoustic propagation channel). In order to improve our estimation, we implemented and tested another algorithm dedicated to estimate the number of telecommunication transmitted signals. The authors of [Chen et al. 1996] used two sets of receiver antennas $X_1(n)$ and $X_2(n)$ with $N_1 > p$, (respectively $N_2 > p$), components. The main idea of Chen's algorithm consists on using the rank the covariance matrices and the cross-covariance matrix of $X_1(n)$ and $X_2(n)$. A main advantage of the last algorithm compared to previous approaches is that this algorithm can be applied even though the noise is spatially correlated and that it gives a confidence level for the estimated number. The main drawback is the computational effort and with ($2N$ + 1) receivers; one can only estimate a source number up to N. In our actual project, more sophisticated algorithm should be developed

Source Localization

Experiments realized in Canada show that using an array of hydrophones, it is possible to detect and give an estimation of the localization of marine mammals [Roy et al.]. Also, using only one hydrophone, [Aurbauer et al. 2000] proved that it was possible to find the distance and depth of marine mammals in particular conditions (shallow water, presence of multiple paths, in the acoustic signal of dolphin whistles, etc.)

On the other hand, in a previous work, we were involved in the application of signal processing along with Independent Component Analysis (ICA) in robotics and artificial life as in auditory scene analysis.

[1] What is the number of sources that are generated by waves? A school of small fishes or sea animals, like shrimp, can generate similar sounds which are dispersing in space. Even artificial noises, like the noise of moving boat, can be obtained from different sources located at various parts of the boats such as the boat propeller, the engine noise, sailors' activities, boat's wake, etc.

[2] In an instantaneous mixture, the observed mixed signals can be considered as the result of a matrix product between a constant real or complex matrix representing the channel effects and the original sources.

Our major task was to improve the auditory capacity of smart robots. These robots, using sound localization, discrimination along with sound separation among other capabilities, imitated the behaviour of human been. By using a set of three microphones, we were able to localise the position of a speaker. Even though sounds produced in air share few characteristics (non-stationarity, sparness) with the underwater generated acoustic signals; they are different in so many ways (frequency, propagation properties, origins, speed, refraction, etc). Our previous experiences can be helpful for us in order to develop new concepts and algorithms to handle this situation. The fact should be emphasized that the localization of underwater acoustic sources can suffer from the drawbacks listed in the previous section of the estimation of source number. It was aimed to develop new underwater localization algorithms based on MIMO systems, modified MUSIC algorithms, High Order Statistic, Channel Equalization algorithms, Time Difference of Arrival, Triangulation, etc.

These algorithms should be tested on real data recorded with the fixed cabled observatory MeDON[3] located near Brest (France) at 20 meter depth. This observatory contains, among other sensors, three hydrophones, and localization of marine mammals should be then possible.

Estimation of High Order Statistics

High Order Statistics (HOS) is used in many localization, identification and separation algorithms. In order to exploit spatial diversity, many blind or semi blind separation; or identification algorithms use HOS, in time or frequency domain. HOS denotes an infinite set of high order moments and cumulants. The nth order moment, $\mu_n(X)$, of a random variable (RV), X, is the mathematical expectation of the nth degree monomial of X:

$$\mu_n(X) = E(X^n)$$

The nth order cumulant, $Cum_n(X)$, is the mathematical expectation of an nth degree polynomial of X [Kendall 1961]. The moments (respectively the cumulants) can be found in the Taylor expansion of the first (respectively second) characteristic functions of X. The nth order cumulant of X can be evaluated a polynomial function of its moments of order less than and equal to n by using the Leonov–Shiryayev formula:

$$Cum(X_1, \cdots, X_n) = \sum (-1)^{k-1}(k-1)!\, E\left(\prod\nolimits_{i\in\gamma_1} X_i\right) * E\left(\prod\nolimits_{j\in\gamma_2} X_j\right) \cdots E\left(\prod\nolimits_{k\in\gamma_m} X_k\right) \quad (6)$$

where the addition operation is over all the set of ($1 \le i \le p \le n$) and comprises a partition [Papoulis 1991] of $\{1, \ldots, n\}$. If the estimation of the moments can be done using unbiased estimators (low pass estimators, direct or adaptive ones), there is few unbiased estimators of cumulants. For this reason, the estimation of cross cumulants and moments, up to the fourth order, has been investigated in our previous studies [Martin 2004, Mansour 2013]. In the latest study, a new adaptive HOS estimator was proposed for fourth order cross-cumulants between X and Y:

$$\begin{aligned} C_N = {} & \frac{N-2}{N}\gamma C_{N-1} + \frac{1}{N}\gamma \mu_{13}(X,Y) + \frac{N+2}{N(N-1)}\gamma x_N y_N^3 \\ & - 3\gamma x_N y_N \mu_{02}(X,Y) - 3\gamma y_N^2 \mu_{11}(X,Y) \\ & + (1-\gamma) x_N y_N^3 - 3(1-\gamma) x_N y_N \mu_{02}^2(X,Y) \end{aligned} \quad (7)$$

Where the forgotten factor $0 < \gamma < 1$, N stands for the number of iterations, C_N is the $Cum(X, Y, Y, Y)$ at the Nth iteration, x_N and y_N are the Nth samples of X and Y, the $(n+m)$th order cross moment at the Nth iteration, $\mu_{nm}(N) = \hat{E}(X^n Y^m)$, is given by the following equation:

$$\mu_{nm}(N) = \frac{1}{\lambda^N}\left(\lambda\left(1-\lambda^{N-1}\right)\mu_{nm}(N-1) + (1-\lambda)\, x_N^n y_N^m\right) \quad (8)$$

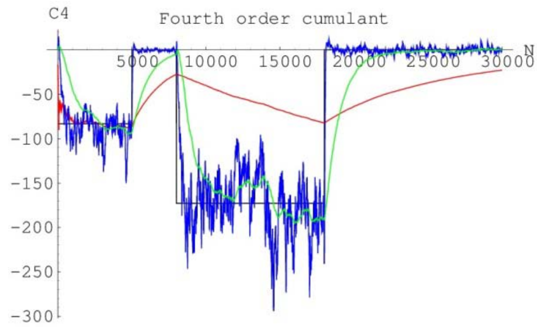


FIG. 9: A COMPARISON BETWEEN THREE DIFFERENT ESTIMATORS OF 4TH ORDER CUMULATES OF A NON-STATIONARY SIGNAL WHICH CONTAINS 4 PARTS (2 UNIFORMS AND GAUSSIANS RV WITH DIFFERENT AMPLITUDE).

Many simulations were conducted to elaborate our 4th order cross cumulant unbiased estimator. Our experimental studies showed that this estimator can be applied on underwater acoustic signals which are non-stationary signals. In some cases, x_N and y_N in the cumulant equation have been replaced by their average over a small estimation window, (10 to 50 samples). The above proposed estimators can be

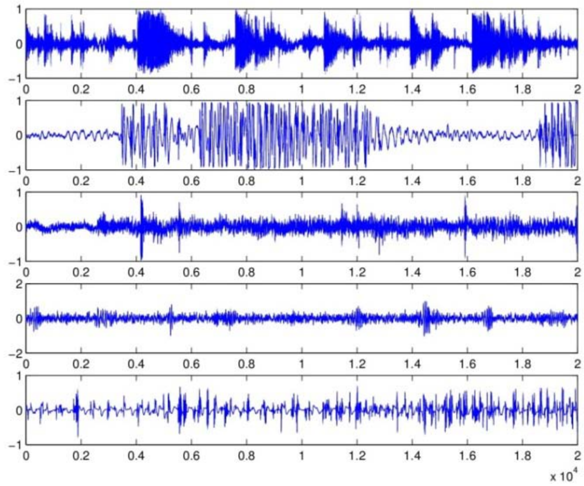
[3] http://www.medon.info/

improved by considering non iid samples. The improvement of the above estimator will be considered in a future work.

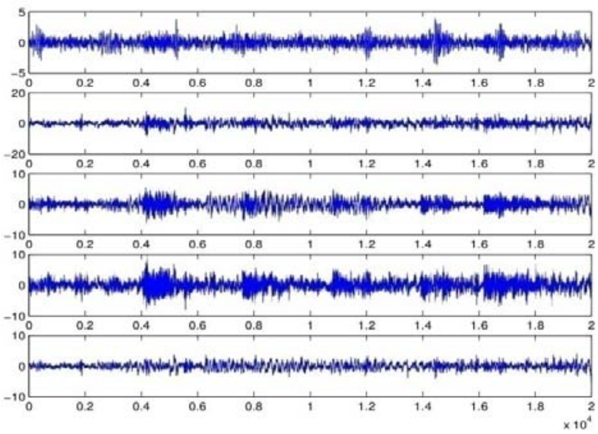
Source Separation

As mentioned before that the assumption about the existence of a single emitter is a kind of luxury that we cannot afford in any real underwater coastal activities, especially in passive mode. In this context, blind source separation algorithms can be of great interest to help achieve better results using passive mode of sensing. In our laboratory, a feasibility study has been previously conducted to separate sources in the context of passive tomography. In that study, it was shown that the acoustic signals have the following properties:

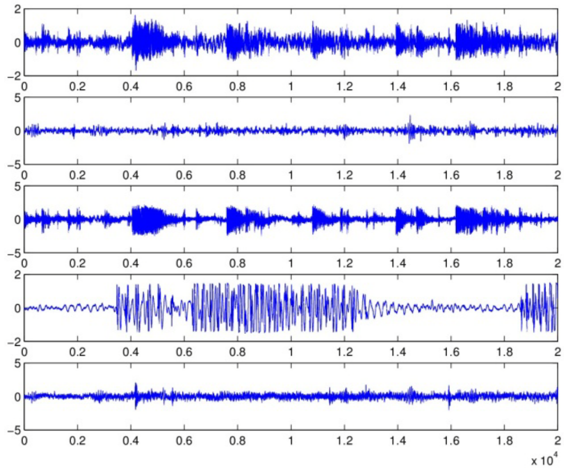
- They are not Gaussian signals which justify the separation performance of algorithms based on higher order statistics.
- Signals are close to speech signals in the direction of non-stationarity and a long-term short-term stationarity.
- Often these signals are sparse (Sparse signal).



a) Original sources.



b) Mixed signals.



c) Separated signals.

FIG. 10: BLIND SEPARATION OF AN INSTANTANEOUS MIXTURE OF 5 DIFFERENT ACOUSTIC SIGNALS (SNAPING SHRIMP, MARSOUIN, BOATS, ETC.). THE USED ALGORITHM IS BASED ON GEOMETRICAL CONCEPTS, FURTHER RESULTS CAN BE FOUND IN [BABAIE-ZADEH 2006, MANSOUR 2002, PUNTONET 2002].

Using our database and the above proposed model of acoustic propagation channel, we performed many simulations. Our experimental study showed that:

a) The source separation methods can be used in our project.
b) Among the blind separation algorithms, those who exploit the statistics of order higher than two have given good results.
c) In instantaneous mixtures, other algorithms can be considered including those who exploit signal characteristics (not iid, non-stationary, Sparse).
d) Algorithms which have been optimized for telecommunications signals did not give us satisfaction.

In a more recent study [mansour 2013], it was confirmed that several separation algorithms have simply failed and this is partly due to the particularity of underwater acoustic channel and secondly the nature of acoustic signals. Best experimental results were obtained using a complete architecture processing modules with pre/post-treatment and cascading two convolutive mixture separation algorithms based on two different frequency criteria. The strategy chosen to lead our next study is to develop or implement source separation algorithms dedicated to acoustic signals and transmission channels. Indeed, future work in this context must always consider both the two main characteristics of acoustic signals i.e. non-stationarity and sparseness.

Performance Indexes

A common factor of all underwater acoustic signals is that all of them are non-intelligible for human been. This property should be taken into account in all stages of signal treatment. In fact, a shifted and filtered sound of whales can be considered by non-experts to be very close to the original signal. In many situations, we are unable to clearly distinguish between original signals and modified ones. This can generate a problem related to measure performance of our algorithms. For example, using our ears, we can easily distinguish the separated speech signals and therefore sort used blind separation algorithms according to their performance. To consider non-intelligible signals, one should investigate performance indexes that can be apply in our project.

In our laboratory, a preliminary study proposed and modified various performance indexes to deal with non-intelligible signals such as noises of boats or marine animals.

A large number of ICA algorithms can be found in the literature to solve the blind source separation (BSS) problem. Most of these algorithms are dedicated to the separation of instantaneous, (i.e. echo free), channel. In our application, the underwater acoustic propagation channel can be modelled by a convolutive mixture, (i.e a multi path and a MIMO finite impulse response (FIR) channel with huge filter order ≥ 2500). It is well known that a blind separation of statistically independent sources of convolutive mixtures can lead us to the original sources up to a permutation and a scalar filter.

$$x(n) = a(z) * s(n) + b(z) * r(n) \tag{9}$$

where $r(n)$ represents a residual mixture of noise and all sources except the one of interest $s(n)$, $a(z)$ and $b(z)$ are residual separation filters and * stands for the convolution product. The main objective of BSS algorithm is to increase the power ratio between the two terms of the estimated signal $x(n)$. In addition, the identification or classification of underwater acoustic signals is extraordinarily difficult step because these signals are non-stationary and non-intelligible sparse signals with low variable kurtosis[4]. In this context, the classification of ICA algorithms according to the separation quality becomes a difficult and important task.

The following discrimination criteria can be optimized to maximize the spatial diversity or the independence among estimated signals. At the same time, they can be very useful to quantify the separation achievement. In the last case, these criteria are called performance indices:

Modified crosstalk: The crosstalk is the inverse of SNR and it is widely used as a performance index for BSS algorithms of instantaneous mixture. To apply the crosstalk, one should have original sources. Therefore, this performance index cannot be applied in real situation where sources are unknown. However it is very useful in simulations. On the other side, it is well known that sources can be separated from a convolutive mixture up to a permutation and up to a scalar filter. Therefore, the crosstalk definition is useless for the BSS convolutive mixture, since it doesn't take into consideration the power ratio between the filtered version of the signal $\xi 1 = a(z) * s(n)$ and the residual error $b(z) * r(n)$. For this reason, we developed a modified definition for the crosstalk as normalized distance between the estimated signal $x(n)$ and the original signal $s(n)$:

$$Mc(\hat{s}(n), s(n)) = 10\log_{10}\left(\frac{E(x(n) - h(z) * s(n))^2}{E(s^2(n))}\right) \tag{10}$$

where the estimated residual filter h(z) is given as the minimum the least mean square (LMS) error ξ:

$$h(z) = \min_h E(x(n) - h(z) * s(n))^2 = \min_h \xi \tag{11}$$

Our experimental results show that for a low order channel filter, (<20), this performance index can be used efficiently. When the order of channel is larger than 20, computing time becomes a big issue.

Mutual information: According to [Tan 2001], mutual information is one of the best independence indices. In the context of BSS problem, the joint and the marginal PDF are unknown but they can be estimated. To estimate the MI, we used a method proposed by Pham [Pham 2003] in which the integral is replaced by a discrete sum and the PDF is estimated using kernel methods.

Quadratic dependence: To measure the independence among the components of a random vector X, the authors of [Rosenbalt 1975] made a comparison between the joint PDF of the vector X and the marginal PDF product of its components x_i. Using similar approach, Kankainen [Kankainen 1995] proposed the quadratic dependence measure $D(X)$ which is a comparison between the joint first characteristic function (FCF), and the product of the

[4] The kurtosis is a normalized fourth order cumulant.

marginal FCF. If the components of X are independent in their set, then, the joint FCF is equal to the product of the marginal and $D(X) = 0$. The main drawback of such performance index is the important computing time.

Non-linear Kernel decorrelation: Bach and Jordan [Bach 2003] proposes an independence measure based on the concept of non-linear decorrelation or the Φ-correlation function ρ_Φ:

$$\rho_\Phi = \max_{f,g\in\Phi}\left(\frac{Cov\left(f(X),g(Y)\right)}{\sqrt{Var\left(f(X)\right)Var\left(g(X)\right)}}\right) \quad (12)$$

Where Cov and Var are respectively the covariance and the variance functions, Φ is a vectorial space of all functions applied from ℝ to ℝ which contents all Fourier transform basis, (i.e. the exponential functions exp (jωx), with ω ∈ ℝ). $\rho_\Phi = 0$ means the independence between X and Y. According to Bach and Jordan [Bach 2003], the best choice of the two non-linear functions f and g can be done using Mercer Kernel functions[5]. We should notice that for acoustic signals better results are obtained using polynomial kernel which gives us a maximum difference between independent and correlated signals. Our experimental studies show that this performance index can be applied successfully in our project. However, computing time and needed memory become extremely important when the number of samples is over 500,000 samples. Finally, the difference between the NL-decorrelation of the sources and the mixed signals depends on original signals, the chosen kernel, as well as, the mixing model and parameters.

Simplified non-linear decorrelation: Using similar approach to [Bach 2003], we proposed a simplified performance index based on the concept of a non-linear covariance matrix $\Lambda = (\rho_{ij})$ defined by:

$$\rho_{ij} = \max_{f,g\in\Phi}\left(\frac{E\left(\langle f(x_i)\rangle_C, \langle g(y_j)\rangle_C\right)}{\sqrt{E\left(\langle f(x_i)\rangle_C^2\right)E\left(\langle g(x_i)\rangle_C^2\right)}}\right) \quad (13)$$

where $X = (x_i)$ is a random vector, $f(x)$ and $g(x)$ are two non-linear functions, and $\langle X\rangle_C = X - E(X)$. If the components of X are independent from each other, then, Λ becomes a diagonal matrix. Using the last definition, we suggest the following performance index:

$$NLD = 20\log_{10}\left(\frac{\|Off(\Lambda)\|^2}{\|diag(\Lambda)\|^2}\right) \quad (14)$$

Here $diag(\boldsymbol{M})$ is a diagonal matrix which has the same principal diagonal of matrix $\boldsymbol{M}$ and $Off(\boldsymbol{M}) = \boldsymbol{M} - diag(\boldsymbol{M})$. Functions f and g are chosen from a set of functions (such as Gaussian kernel, 6th order polynomial Kernel whose coefficients are the components of a unitary vector, saturation kernel using arc-tangent function, saturation kernel using hyperbolic tangent function). Our experimental studies show the effectiveness of this performance index to deal with underwater acoustic signals and channels. The main drawback of this performance index is that obtained values depend on the kind and the number of original independent signals. Therefore, this performance index can only be used in simulations where the original sources are known.

Independence measure based on the FCF: The joint FCF of a random vector X is equal to the product of the marginal FCF of its components if and only if they are independent from each other. Using that property, Feuerverger [Feuerverger 1993] proposed the following independence measure:

$$\begin{aligned} T = {} & \frac{\pi^2}{\eta^2}\sum_{ij} g\left(X'_j - X'_i\right)g\left(Y'_j - Y'_i\right) \\ & - \frac{2\pi^2}{\eta^3}\sum_{ijk} g\left(X'_j - X'_i\right)g\left(Y'_j - Y'_k\right) \\ & + \frac{\pi^2}{\eta^4}\sum_{ijkl} g\left(X'_j - X'_i\right)g\left(Y'_l - Y'_k\right) \end{aligned} \quad (15)$$

where g is an adequately chosen function [Feuerverger 1993], $X' = \Phi^{-1}\left(\frac{8X-3}{8\eta+2}\right)$ is the approximation of the score function of X, and $\Phi(X)$ is the PDF of zero mean and unite variance Gaussian signal. Our experimental studies show that the computing time is the main drawback of this performance index. We should mention that for stationary signals, this performance index is consistent. Unfortunately, the last interesting property is useless in our application since the acoustic signals are non-stationary signals.

Cross-cumulants: Previous described performance indices cannot be applied in real situations, where original signals are unknown because the performance values depend on the sources. Therefore, we

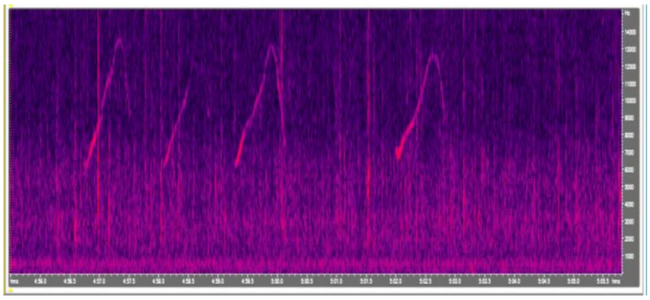
[5] A bilinear function K(X, Y) from a vectorial space X, (for example $\mathbb{R}^m$) to ℝ is said to be a Mercer kernel if and only if its Gram matrix is a semi-positive matrix. By definition the Gram matrix of basis vectors, (X1, . . . , Xm), of a m dimensional vectorial space X with respect to a bilinear function K(X, Y) is the matrix given by Gij = K(xi, yj). K(X, Y) should, also, have the translation invariance, the convergence in $\mathcal{L}^2(\mathbb{R}^m)$ and isotropic properties. A possible kernel is the Gaussian kernel.

developed a new performance index based on is the average the 4th order cross-cumulant Cum(1,3)(X, Y)[2] which is obtained using a sliding estimation window. Good results have been obtained using this performance index on instantaneous or convolutive mixtures of acoustic signals. However, the computing time is relatively important.

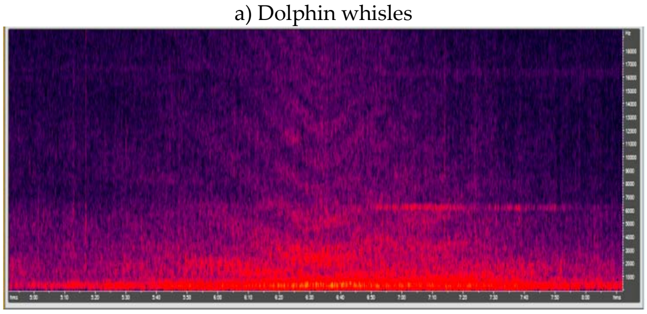
Source Classification, Recognition and Identification

Once the sources have been separated, another important stage of our project will be followed. This important stage consists on performing source classification, recognition and identification. The classification part will divide the received signals into several families (artificial signals, fishes, underwater mammals, natural noises, etc.). Once the family of a signal is found, a recognition algorithm should be applied to specify the type of the signal (boat, submarines, dolphins, etc.). Finally, an identification stage will be an extra. In this stage, one could identify a specific boat or the activity of a submarine (at the surface, an immersion, etc.). To reach our goals, we are planning to apply feature extraction, hidden Markov models, classification algorithms, etc. Previous studies showed us that classic signal processing algoritms along with classification tools have shown their limitation to deal with highly non-stationary and sparseness signals. In order to deal with such signals, we are planning to develop new blind identification algorithms, along with multi-space representation tools.

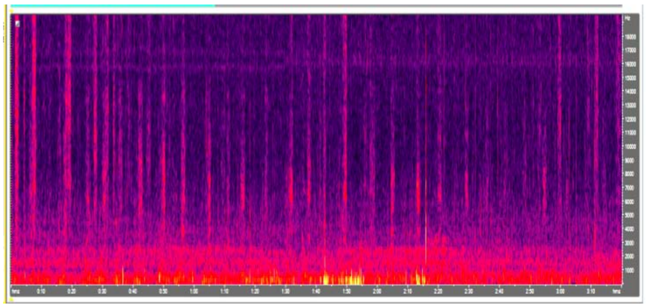
Fig. 11 gives an example of few indentified sources recorded with hydrophones on MeDON Observatory.



a) Dolphin whisles



b) Lloyd's Mirror coming from boat sound



c) wide band signal of a diver

FIG. 11 SPECTROGRAMS COMPUTED WITH HYDROPHONE DATA RECORDED ON MEDON OBSERVATORY

Video Surveillance

It has been mentioned before that our underwater surveillance system contains different types of cameras. Our vision system will contain infra red camera, microscopic and macroscopic cameras， as well as different spectre light projectors (white, red, infrared lights). The light systems will be most of the time in off position. However, one or all of light projectors can be switched on whenever it becomes necessary. The white light helps us getting nice photos within short distance (less than 20 meters), the red and the infrared lights are useful to get image without disturbing biological life. It worth mentioning here that underwater images could suffer from main following limitations:

- Light level
- Water turbidity
- Sampling and memory
- The problem of image analysis
- Data compression
- Artifacts associated with sensors, movement, lighting control, etc.

In previous projects, we were involved in the construction of an Unmanned Aerial Vehicle which was containing stabilized camera, infrared camera, UV camera, few other sensors (GPS, thermometer, barometer, air-pollution-monitoring-sensor, etc.). Using such UAV to get several aerial photos of coastal regions, it can increase the efficiency of our approaches; aerial photos along with bio-signals should be processed. At this stage of our project, we will work on image processing and combining different approaches proposed at the different parts of the project. We should also merge and integrate the outlines of the whole system. The latest combination could be done using data fusion methods. A natural extension to our project can be the application of

satellite remote sensing, airborne hyperspectral remote sensing, hyperspectral in situ sampling, in-water hyperspectral profiling, sea gliders supported by water sample analysis (eg cytometry signal analyser) to study the flux of in-water pigments, coloured dissolved organic matter and sediments in esturine systems and their movement, transformation and destination as they move into adjacent coastal waters.

Multitude and Diversity of Sensors

In our project, we are planning to deploy different sensors and data acquisition systems, such as: Sonars, ADCP, hydrophones, cameras, sensitive microscopic digital cameras. At a final stage of our project, other sensors will be added such as, see future works section: Cytometer, sensitive digital cameras, satellite image data acquisition, etc.

As it was mentioned before that this project will be a multi-disciplinary project, members of our team should conduct their research respectively in the following fields:

- Bio-Engineering to study, analyse the samples and interpret the final results.
- Acoustics, in order to propose the most adapted sounders, sonars or hydrophones according to the underwater configurations and the studied ecosystem
- Signal processing to propose and develop new blind identification algorithms.
- Pattern Recognition to help classify the samples and automatically extract useful information.

As mentioned before, this project requires a considerable amount of complex and extensive experimentation, along with associated routine laboratory work, as well as detailed theoretical planning and interpretation. Data should be recorded with several possible platforms such:

- Vessels
- AUV (Autonomous Underwater Vehicles) or ROV (Remotely Operated underwater Vehicles),
- Moorings
- Seafloor observatories

Therefore, we should conduct experiments, collect data and process the obtained data. In addition, we will implement various developed approaches in real time processing algorithms. We should also merge and integrate the outlines of the whole system. The latest combination could be done using data fusion methods based on:

- Information Extraction
- Harmonization of information
- Data Fusion

Fig. 12 shows an example of hydrophone and ADCP data recorded on the MeDON observatory at the same time.

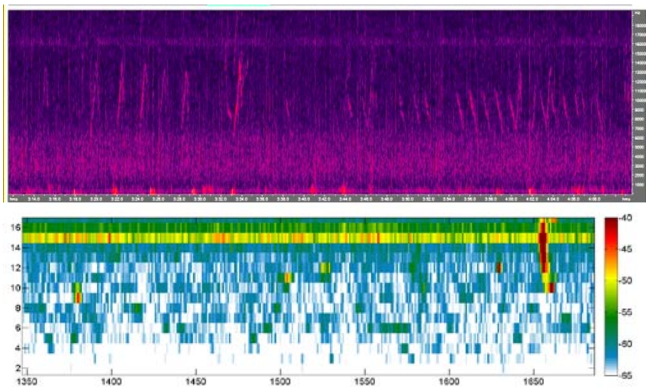


FIG. 12. SPECTROGRAM OF HYDROPHONE DATA (TOP) AND ADCP BACKSCATTERING DATA (DOWN) RECORDED ON MEDON OBSERVATORY AT THE SAME TIME (2012/06/20 10H05 PM TO 10 H10 PM)

Conclusions

At this early stage of our project, it is tough to make general conclusions. However, as our team and our partners have been approaching the project from different academic and engineering points of view, partial conclusions can be made on every part.

Following our studies, it can be concluded both that the separation of passive acoustic signals from a sound channel is possible, against the separation quality depends on several parameters. On the other hand, it was found that the performance can be greatly improved by considering the characteristics of acoustic signals.

Also, using active acoustic signals coming from echosounders, we proved in previous works that these data should be used for several applications and not only fishes stocks evaluation, such algae monitoring or bubbles seeps quantification.

So, using at least both active and passive acoustic sensors, and other sensors like cameras, we should be able to propose an ecosystem or a port monitoring system.

To conclude, in this article, several signal processing contributions applied on real world application such as passive or active acoustic signals, have been

presented. Many simulations have been conducted and experimental studies showed the necessity of considering pre-processing and post processing of observed signals.

Future Works and Platform Extension

It is amazing to know that the health of our planet could depend on very small organisms such as the plankton (an old Greek word planktos means wanderers) which are two types of microscopic organisms: phytoplankton (plants), and zooplankton (animals). These microorganisms live in the sea and ocean and are very important to the whole planet. In fact, they are the base of marine food chain: small fish and whales depend on the plankton to survive. On the other hand, small fish are the food for bigger fish. It is obvious fish is an important food reserve. Many people around the globe depend on fish market and food.

According to recent studies, as far as 70% of the oxygen that we breathe is produced by marine life. Most of that oxygen is directly produced by phytoplankton. For these reasons, the European Union classified the health of phytoplankton as a major priority (Directive CE2000).

In an advanced stage of our project, we can include an improved method of monitoring coastal marine ecosystems, using signal-processing technologies to monitor marine Micro-Organisms (MO) that have a major role in those ecosystems. Because MO is affected by many parameters, including water temperature, water pollution and salinity, such monitoring will assist the modelling of coastal climate changes or the study of the marine food chain. We will extend our study to include various other marine micro-organisms (such as coral, etc.) and/or study specific marine ecosystems such as coral reefs, rivers and lakes. This study will focus on processing cytometry signals and the outputs of other sensors to assess the role of MO in monitoring these ecosystems. In order to carry out our study, water samples will be regularly collected and analysed. The analysis is based on electrical-fluorescent signals, microscopic images, and satellite images. It is well known that the obtained electrical-fluorescent signals are random non-stationary. In this situation, classical signal processing algorithms can hardly give satisfactory results. Therefore, appropriate new signal and image processing algorithms should be developed. Results of this study should be linked to multifrequency acoustic data recorded with echosounders or acoustic profilers, which are able, using inverse modelling tools, to give an estimation of zooplankton abundance.

Other acoustic sensors, like multibeam sounders or subbottom profilers should be used, in order to obtain data in a larger scale and/or other part of the seafloor.

Using UAV to get several aerial photos of coastal regions, it can increase the efficiency of our approaches; aerial photos along with bio-signals should be processed. In addition, Satellite images will be considered to achieve very large-scale monitoring. These data will give a complement of data recorded with underwater platforms such vessels, moorings, seafloor observatories, ROV AUV and landers. These different platforms should be used independently or not: for example, landers can be associated to a seafloor observatory, which can allow the lander an easier exchange of data to users, new mission planning or communication between the different sensors. This last point can be seen, among other things, as a kind of fusion work: for example, we can imagine a sensor which would record data only when another sensor would detect a particular signal.

All these platforms can be equipped with many different sensors: acoustic and video of course, but also chemical sensors (oxygen or nitrate detectors, etc.), physical sensors (like pressure or temperature sensors), etc. Especially, electrical field and magnetic sensors can be also considered as part of our future system. Our vision is to mimic natural underwater predators such as: sharks (they are dotted with electrical sensors), dolphins (they are using advanced 'sonar'), coral and shells (they use chemical detectors), or octopus (they using big eyes).

Finally, it is worth mentioning that fish is a major food supply cultivated from seas and oceans in all around the world. While it is abandoned now in our neighborhood markets, failure to take preventative actions to preserve this food supply, eventually it vanishes. Once vanished, it will be extremely challenging to recover. Efforts in this project will be paid to design a system and establish processes based on proven technologies that ensure a sustainable fish supply.

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Ali MANSOUR was born at Tripoli in Lebanon, on October 19, 1969. He received his M.S degree in the electronic electric engineering on September 1992 from the Lebanese University, his M.Sc. and Ph.D. degrees in Signal, Image and Speech Processing from the "Institut National Polytechnique de Grenoble-INPG (Grenoble, France) on July 1993 and January 1997, respectively, and his HDR degree (Habilitation a Diriger des Recherches. In the French system, this is the highest of the higher degrees) on November 2006 from the Universite de Bretagne Occidentale-UBO (Brest, France). His research interests are in the areas of blind separation of sources, high-order statistics, signal processing, passive acoustics, cognitive radio, robotics and telecommunication.

From January 1997 to July 1997, he held a POST-DOC position at Laboratoire de Traitement d'Images et Reconnaissance de Forme (INPG Grenoble, France). From August 1997 to September 2001, he was a RESEARCH SCIENTIST at the Bio-Mimetic Control Research Center (BMC) at the Institut of Physical and Chemical Research (RIKEN), Nagoya, Japan. From October 2001 to January 2008, he held a TEACHER-RESEARCHER position at the Ecole Nationale Supérieure des Ingénieurs des Etudes et Techniques d'Armement (ENSIETA), Brest, France. From February 2008 to August 2010, he was a SENIOR-LECTURER at the Department of Electrical and Computer Engineering at Curtin University of Technology (ECE-Curtin Uni.), Perth, Australia. During January 2009, he held an INVITED PROFESSOR position at the Universite du Littoral Cote d'Opale, Calais, France. From September 2010 till June 2012, he was a PROFESSOR at University of Tabuk, Tabuk, KSA. He served as the ELECTRICAL DEPARTMENT HEAD at the University of Tabuk. Since September 2012, he has been a PROFESSOR at Ecole Nationale Supérieure de Techniques Avancées Bretagne (ENSTA Bretagne), Brest, France. He is the author and the co-author of three books:

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He is the first author of several papers published in international journals, such as IEEE Trans. on Signal Processing, Signal Processing, IEEE Trans. on Wireless Communication, IEEE Trans. On Antennas & Propagation, IEEE Signal Processing Letters, Neuro Computing, EUROSIP Journal on Advances in Signal Processing, IEICE and Artificial Life, Robotics, etc.. He is also the first author of many papers published in the proceedings of various international conferences.

Finally, Dr. Mansour was elected as the grade of IEEE Senior Member in February 2006. He has been a member of Technical Program Committees (TPC) in many international conferences. He was chair, co-chair and a scientific committee member in various international conferences. He is an active reviewer for a variety of international journals in different engineering fields. He was a Lead Guest Editor at "EURASIP Journal on Advances in Signal Processing - Special Issue on Signal Processing Methods for Diversity and Its Applications".

Isabelle Leblond was born in France, near the town of Rouen, on November 1st, 1977. She obtained the "baccalauréat" (equivalent A-level) in science in Rouen in 1995. Then, she successively obtained the the fourth years university degree in Physics at the University Paul Sabatier of Toulouse (France) in 1999 and the fifth years university degree in Oceanography at the University of Bretagne Occidentale of Brest (France) in 2000.

Finally, she obtained her PhD in Signal and Image Processing at the University of Bretagne Occidentale in 2006.

She worked at Ifremer (French Institute of Marine Research) in three different projects: 1/implementation of ecological and hydrodynamic model of Bay of Brest in 2000, 2/studies of algae in water column with fisheries sounders from August 2007 to December 2008 and 3/acoustic characterization and quantification of fluid seeps in water column from August 2009 to December 2010 (Isabelle Leblond, Carla Scalabrin, Laurent Berger, Louis Géli. Acoustic monitoring of gas emissions from the sea floor: estimation of bubbles volumetric flows by inverse modeling, in preparation). She also worked at Ecole Navale (French Military Naval Academy) from April 2006 to July 2007 in the research field of sediment profilers and at IRD (Institue for Research and Development) in 2011 in acoustic modeling of backscattering of zooplankton.

In addition, she worked at Ensta Bretagne (ex Ensieta, French State Graduate and Research Institute located at Brest, France) in three projects: 1/long-term sonar image registration from September 2002 to april 2006 (PhD thesis project, see I. Leblond, M. Legris, & B. Solaiman, Use of Classification and Segmentation of Sidescan Sonar Images for Long Term Registration, IEEE OCEANS'05 EUROPE, Brest, France, 20-23 Juin 2005), 2/multi-view classification of manufactured objects in 2009 (see I. Leblond, Cécile Berron, Isabelle Quidu. Mise en oeuvre de stratégies prédictives sur les vues à acquérir pour la classification multi-vue d'objets immergés à partir d'images SAS. Conférence RFIA'2010 Reconnaissance des Formes et Intelligence Artificielle, du 19 au 22 Janvier 2010, Caen) and 3/ signal processing and fusion of data coming from several sensors (passive and active acoustics, video) for long-term monitoring since September 2011. This last subject if the actual current job.

Her major field of research is in underwater acoustics, signal and image processing associate to sonar and hydrophone data.